# Are my kids going to eat it? Sensory analysis mediated by spectroscopic data to predict adolescent food choices

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**Abstract.** In this work, we present a procedure that combines the sensory analysis outcome and the spectroscopic data collected in the NIR region. This method allows for a complete characterization of each sample before ingestion without any alteration of its composition or appearance. NIR spectra of hundreds of samples for each of the parameters evaluated have been collected. The samples were then analyzed by conventional analytical procedures, using a texture analyzer, a refractometer, and an electric conductivity meter. Moreover, a spectrum of each sample was recorded prior to the ingestion. Spectroscopic data from the large datasets built for each of the characteristics evaluated have been used to build iPLS prediction models. These models have been later used on the spectra of the samples that underwent sensory analysis to predict their composition. With this a priori knowledge it was possible to understand the textural, and flavor combinations liked by the panel of adolescents involved in the hedonistic analysis performed.

## 1 Introduction

Agriculture is facing the threat of climate change. Introducing varieties that tolerate reduced hydric availability seems a viable solution to cope with climatic instability. In the ongoing breeding program at the Italian research centre of CREA-VE (Turi, Apulia region), several new table grape varieties have been created. Some of them will be released soon on the market. A selection for plants resilient to water restriction has been performed on these novel varieties. If the observed resilience would ensure the production of grapes, this does not translate into consumers' acceptance of the new products. Adolescents and young adults tend to consume less than the recommended amount of fruit and vegetables [1]. Offering the grape producers drought-resistant varieties with traits especially appreciated by picky eaters is an added value for any novel variety. An a priori knowledge of consumer appreciation would support the grape producers' decision of what new drought-resistant variety to introduce in the vineyards. Sensory analysis is the only analytical method available to assess the appreciation of any novel food product. This type of analysis, unfortunately, is not only subjective but more importantly destructive. It is not possible to analyze the samples which are going to be eaten by any conventional analytical method. Therefore, it is not possible to determine the eaten samples specific metabolic composition and texture characteristics. A sensory evaluation in which sensory properties are linked to physical and chemical variables enables the creation of food products with maximum consumer acceptance [2]. Among the emerging sensory and consumer science methodologies the incorporation of spectroscopic techniques in sensory analysis represents a viable option for novel product valorization [3]. In this work, multivariate models were obtained with partial least squares (PLS and iPLS) regression to predict parameters not directly measurable on the samples that underwent the sensory destructive testing step. A good prediction ability was obtained for parameters directly linked to the metabolic composition (TSS and TA) which are linked to specific metabolites producing signals in the spectra (mainly the sugars for TSS and acids for TA). For textural parameters prediction, as found in previous works, spectral data needed to be integrated with information on berry shape, density, or size to build effective prediction models.

# 2 Material and methods

## 2.1 Reference methods

The variety selected is a late-ripening one (September-October), characterized by large, uniformly colored red/purple berries without seeds. Each berry was weighted on a digital scale prior to any measurement. Around 200 berries were used to measure total soluble solids content (TSS, °Brix) and total acidity (TA, g/l as tartaric acid) using a digital refractometer Atago PR1 (Atago Co., Tokyo, Japan). TA and TSS were measured in triplicate at 20 °C. Around 150 berries were used to measure texture parameters. The instrumental Texture Analysis was performed with an XforceP texture analyzer (Zwick/Roell GmbH &Co., Ulm, Germany) equipped with the Zwick Roell software package (testXpert II Zwick/Roell, vers. 3.31 Ulm, Germany). As previously described [4]. Hardness (N, as P1), springiness (mm, as d), cohesiveness (adimensional, (A2+A2w)/(A1+A1w)), gumminess (N, as hardness*cohesiveness) and chewiness (mJ, as gummines*springeness) were automatically calculated by the software [5]. The equatorial diameters of the berry were also provided by the software as the distance between the two probes when the second probe touches the surface of the berry. For the berries used for TA, TSS, and texture measurements NIR spectra on three different berry's faces were measured prior to the primary methods analyses. For each berry a mean spectrum obtained from the average of the three different berry faces spectra was employed in the modeling step. The FT-NIR spectrophotometer employed was a TANGO (Bruker, Germany). The absorption measurements were performed in diffuse reflection mode. The spectra were collected by the OPUS/QUANT software version 2.0 (Bruker Optik GmbH, Ettlingen, Germany) between 12,000-4000 $cm^{-1}$ (833-2500 nm), with 8 $cm^{-1}$ resolution and 64 scans. A CM-5 - Konica Minolta spectrophotometer was also used to collect visible spectra of all the berries between 360 and 740 nm. The chemometric analyses were performed with the statistical software R version 4.1.2 (2021-11-01). The hedonic testing was performed using a 9-point hedonic scale (from 1 "dislike extremely" to 9 "like extremely"), which is the most widely used scale for measuring food acceptability [6]. The panelists received instructions about the scaling systems and procedures before the test.

## 2.2 Prediction models

Different pretreatments were applied to the NIR spectra. Standard Normal Variate (SNV) was chosen for all the parameters apart from TA for which an SNV followed by a first derivative was applied. PLS models built on the whole spectral range did not provide good results (models with $R^2$ way below 0.5 and high RMSEC). Each of the final prediction models was built using the spectral intervals selected by an iPLS. Final prediction models for the taste parameters were optimal for TSS and TA ($R^2$ >0.5 and small RMSEC) but not as good for the texture parameters solely based on the absorbencies of the NIR region wavelength. As found in previous articles, the prediction of textural parameters for grape berries increases its effectiveness when the density class is included as a variable [3]. Anyway, the density measurement involves a further step since it requires the immersion of each berry in saline solutions with different concentrations. The berries floating in each solution are grouped and belong to the same density class [7]. In our experiment, we chose to avoid this step but weighted each berry on a digital scale. The weight of the berry was added to the absorbencies in the NIR region as a variable for the model build-up.

# 3 Results and Discussion

## 3.1 Hedonic tasting

Scoring was generally high, with 72% of tasters rating the berries above 7. None of the tasters selected the lowest scores on the scale, and only three berries were rated below 5. This result shows how the chosen variety was very appreciated by the panel. There was no difference in the rating frequency related to the gender of tasters (data not shown). The lack of differentiation of tasters' liking is an indication of how much the tested variety was very appreciated at the conventional harvest time (late October).

## 3.2 Visual aspect

Color is one of the most important phenotypic characteristics of table grape cultivars, which contributes to the consumer's preference. [Ref]. [Ref] From the visible spectrum for each berry the CIELab color coordinates L* (lightness), a* (red/green, for positive/negative values), b* (yellow/ blue for positive/negative values), and the derived parameters C* (chroma) and H* (hue) were calculated. All the absorbance values were normalized, using the min-max normalization method before the analysis. A principal component analysis (PCA) was performed on the visible spectra of the berry samples used for the hedonic test. In the PCA plot reported in Fig. 1 (total explained variance 80.22) it is possible to individuate berries with a more intense red color placed in the fourth quadrant (higher loadings for peaks around 500 nm) while the third quadrant is the one containing the more bluish berries (higher loadings for peaks around 600 nm). But in general, the PCA plot does not show a neat differentiation among samples based on the absorbance spectra in the visible range. In Fig. 1 the samples are colored based on the scores given by tasters. No difference was found among samples based on the liking score, which indicates that the visual appearance did not seem to have influenced the rating. Even the two samples far away in the fourth quadrant, which indicates a different and more intense reddish color were ranked 7 which was the mean score rating for the samples. A Spearman's correlation test was also performed on the absorbance values of the VIS spectra, L*, a, b, C*, and H* with the hedonic test scores. Unfortunately, no correlation was found among specific spectral peaks or CIELab parameters and the scores of the sensory analysis. These results indicate that consumer satisfaction is not clearly related to the color of the berry.

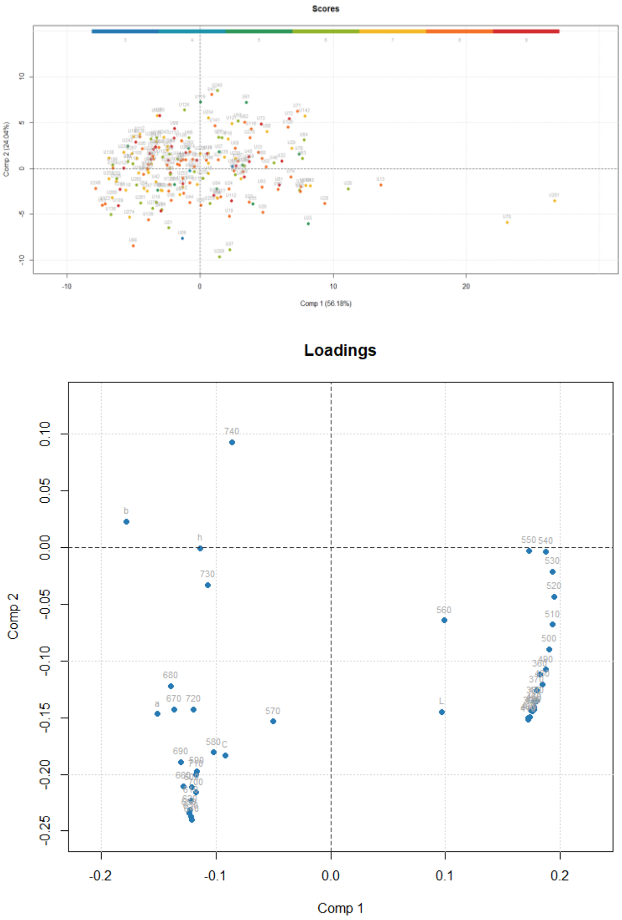


**Figure 1.** PCA score plot with samples coloured by ranking (top) and loading plot (bottom) using visible parameters for the eaten berries.

This outcome could be explained by the lack of a striking difference in the visible spectra or a consequence of the presentation of samples. Indeed, each berry was placed in a small opaque white plastic cup and tasters were asked to randomly pick the cups displayed on a large table. Probably, due to the short time before picking the samples from the cup and subsequent ingestion, the tasters did not have the time to take into consideration the visual aspect of the samples ingested.

## 3.3 Texture and taste

Texture and taste parameters for the berries used in the sensory analysis were predicted with the models built on the NIR spectra (Table 1).

**Table 1.** Mean values and standard deviation for predicted texture and taste parameter.

| Parameter | Value |
|---|---|
| TSS (°Brix) | 21.96± 0.91 |
| TA (g/L tartaric acid equivalents) | 5.63±0.53 |
| Hardness (N) | 0.387 ± 0.046 |
| Springiness (mm) | 0.131 ± 0.005 |
| Cohesiveness (adimensional) | 0.015 ± 0.001 |
| Chewiness (mJ) | 0.233 ± 0.030 |

The PCA performed on textural and taste parameters (cumulative explained variance 67.42, Fig. 2) does not show a grouping of the eaten samples. Indeed, all the berries analyzed in this experiment, both those used as a training set for the models and those for sensory analysis, were randomly selected from bunches collected from the same vineyard at the same time, which ideally should have very similar maturity and chemical composition. Taking into consideration the loadings of the taste parameters TSS (higher on positive PC1 and PC2) and TA (higher on negative PC1 and PC2), the samples in the first and fourth quadrants have the highest sugar and lowest acidic amount, thus can be seen as slightly more ripen compared to those samples in the second and third quadrant which are characterized by the lowest sugar and highest acidic content. Along with sugar accumulation and color development, softening is an important physiological change during the onset of ripening in fruits [8]. Indeed, the texture parameters confirm the split of samples in the PCA as more ripened on the right side and less ripened on the left side. Samples with negative PC2 coordinates show higher hardness which represents the maximum force required to compress the sample in the first instance. Chewiness**,** which is the energy required to chew a solid food until it is ready for swallowing [9] is also higher in less ripened samples on the right side of the plot. Also, springiness, the ability of the sample to recover its original form after removing the compression, is also higher for the less mature samples. Cohesiveness is a parameter that describes how well a food retains its form between the 1st and 2nd chew. In our PCA plot cohesiveness has a higher loading on the positive PC1 axis. With ripening there is a softening of berries, indeed ripen berries with higher sugar content should also be characterized by a softer pulp. We found that this lack of a relationship between sugar content and berry cohesiveness was also observed for the samples used for the reference analysis which showed a higher cohesiveness for higher TSS. Previous articles reported how for some texture parameters the berry volume played a more important role with respect to sugar accumulation [10]. To test this hypothesis, since we do not have data concerning the volume, we introduced the berry weight among the variables employed in the PCA. The berries of the variety employed are uniform in size, shape, and chemical composition thus we could assume that heavier berries are also bigger in volume. Indeed, in Fig. 2 we observe how lighter thus smaller berries show higher cohesiveness.

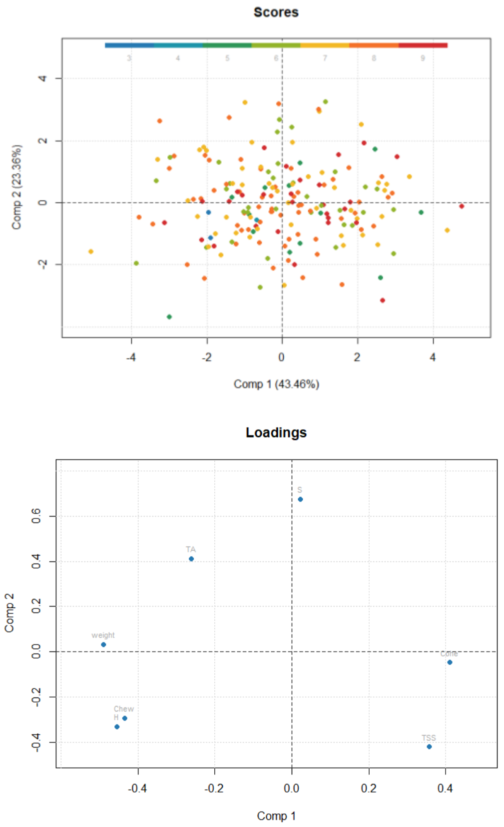


**Figure 2.** PCA score plot with samples colored by ranking (top) and loading plot (bottom) for the predicted texture and taste parameters of the hedonic samples.

In Fig. 1 on the top, the ranking for each berry is indicated with a color gradient. Interestingly the only three low-rated samples (in blue in Fig. 2) are in the second quadrant which is characterized by higher hardness and chewiness which thus could be considered two unfavorable traits.

## 4 Conclusion

In our hedonic assessment, the consumers were involved in the evaluation process to find out the influence of the appearance, taste, and texture of grape berries for a novel drought-resistant grapevine variety. The pool of samples employed was collected from fully ripened samples from the same vineyard. The prediction models showed a homogenous maturity level and similar texture properties for all the berries. This lack of a difference among the tested samples is reflected in the homogenous outcome of the sensory analysis which shows a high appreciation of the variety at that maturity stage. The tasters' panel was predominantly composed of young teenagers who are known to consume smaller amounts of fruit and vegetable compared to the ideal servings. The appreciation shown for the tested variety indicates how this variety could be a good choice for vine growers who are searching for a resistant grapevine. The procedure followed could be applied to other novel varieties to get an insight into the reasons behind the low or high appreciation of a specific variety. In the future, we plan to include flavor components as variables and add questions for the tasters to physiological factors that might play a role in their choice.

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## References

1. V. Albani, L. Butler, W. Traill, O. Kennedy, *Brit. J. Nut.* **117**(5), 759-765 (2017)
2. Sharif Mian, Butt Masood, Sharif Hafiz, Nasir Muhammad. Sensory Evaluation and Consumer Acceptability. In book: Handbook of Food Science and Technology (pp. 362-386) Chapter: Sensory Evaluation and Consumer Acceptability (2017)
3. T. Basile, A.D. Marsico, M.F. Cardone, D. Antonacci, R. Perniola, *Foods* **9**, 98 (2020)
4. T. Basile, A.D. Marsico, R. Perniola, *Foods* **11**(3), 281 (2022)
5. L. Rolle, S. Giacosa, V. Gerbi, V. Novello, *Am. J. Enol. Vitic.* **62**, 49-56 (2011)
6. D.R. Peryam, N.F. Girardot, Food Engineering **24**, 58-61 (1952)
7. M. Pollon, F. Torchio, S. Giacosa, S. Río Segade, L. Rolle, *Food Chem.* **276**, 562-571 (2019)
8. S.D. Castellarin, G.A. Gambetta, H. Wada, M.N. Krasnow, G.R. Cramer, E. Peterlunger, K.A. Shackel, M.A. Matthews, *J. Exp. Bot* **67**(3), 709-22 (2016)
9. S. Kasapis, A. Bannikova, Chapter 2 - Rheology and Food Microstructure, Editor(s): J. Ahmed, P. Ptaszek, S. Basu, In Woodhead Publishing Series in Food Science, Technology and Nutrition, Advances in Food Rheology and its Applications, Woodhead Publishing, 7-46 (2017)
10. P. Abbal, A. Vernhet, Elissa Abi Habib, S. Carrillo, M.A. Ducasse, et al., *Vitis* **59**, 163-168 (2020)